Automated revision of GIS databases

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ABSTRACT

Digital spatial data are underlying strong temporal changes. The typical approach of updating these changes is to check the data manually for their correctness by superimposing them on up-to-date orthophotos. The update cycles of large data sets are in the range of several years. At present shorter update cycles are unrealizable for two reasons. The manual inspection of the data is very cost- and time-consuming and aerial photographs for large areas are very often not available in the needed time intervals. However, a decisive turn can be seen in data availability. With new satellite systems, it will be possible to provide up-to-date high resolution orthophotos in short time periods and high quality in the near future. At September 24th, 1999, the optical high resolution satellite IKONOS, developed by the company Space Imaging (http://www.spaceimaging.com), was brought successfully into orbit. Further systems as for example Quickbird of the company EarthWatch, OrbView 3 and 4 of the company ORBIMAGE or EROS A and B of the company West Indian Space will follow shortly (see also [9, 10]). The data which will be delivered from these new satellite systems will close the gap between existing medium resolution satellite data (as for example Spot, Landsat or IRS-1C) and very high resolution data from airborne systems. In near future users will be able to select images from several providers to use them for their mapping tasks. In order to eliminate the still existing bottle-neck of manual updating of GIS data, the Institute of Photogrammetry (ifp), University of Stuttgart developed a software package which is presented in this article.

Keywords

GIS, update, classification, ATKIS, remote sensing, matching.

1 INTRODUCTION

The process of updating of GIS data can be subdivided into three steps. In the first step, changes of the landscape must be detected. This can be done for example by a comparison of the GIS data with an up-to-date orthophoto or by field inspection. This is a work- and time-consuming process which is at current only barely automated. Furthermore the manual comparison of GIS data and orthophotos requires high concentration and is error-proned.

In the second step, various data sources must be used to add further attributes which cannot be detected in the orthophoto. This can be for example street names, ownership attributes or administrative boarders which have to be retrieved from very different data sources. In order to be able to work effectively an optimization is necessary that assures a fast information and work flow. This optimization is strongly dependent on legal and organizational responsibilities of the data producers and will not be further discussed at this point.

In the last step, the changes with all additional information have to be stored in a GIS database. This operation step can be automated at least in part. Consistency checks can be done with automated checking programs which assure high quality data sets. Many functionality's for this purpose are already integrated in commercial GIS products and further application-specific procedures can be programmed by the users.

The first step of this process – the detection of changes – requires the largest amount of work. In the following an approach is introduced which enables the fully automatic detection of changes in GIS by using of multispectral remote sensing data.

The approach for change detection can be subdivided mainly into two steps (see figure 1). In a first step the remote sensing data have to be classified pixelwise into different land use classes. This is done by a supervised maximum likelihood classification. The problem for an automatic approach is the supervised part of the classification algorithm. Normally this part involves the work of a human operator and requires a lot of experience because the quality of the training areas is a crucial factor for the quality of the classification result. As the digitizing of the training areas is time intensive and new training areas have to be digitized for every new data set (because of atmospheric effects, different spectral diffusion depending on the sunlight, different spectral characteristics of vegetation depending on season or soil, etc.), a method is needed to derive the training areas in an automatic way. Having assumed that the number of wrongly collected GIS objects and the number of changes in the real world are substantially less than the number of all GIS objects of the data set, the training areas can be derived automatically from the already existing GIS data. The higher the quality of the training areas the better will be the result of the classification. Therefore, the object geometry is not used as stored in the GIS database - a pre-processing has to be performed first.

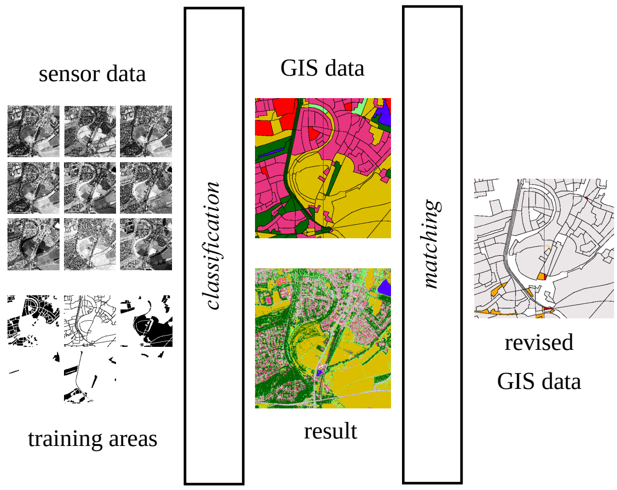


Figure 1: Overview of the approach

After the classification it must be decided which of the GIS objects do not match the remote sensing data. These can be objects where a change in the landscape has occurred or objects that were not collected correctly. All GIS objects are subdivided into three classes. The first class contains all objects which are detected with a high certainty in the remote sensing data, the second class contains all objects which are detected only partly and the third class contains all objects which cannot be detected at all.

2 IMPLEMENTATION

The approach is implemented in a software package based on UNIX and X-Windows. Figure 2 shows a selection of different windows of the program. The software was implemented in such a way that all parameters of the approach can be changed interactively by the user and stored as a project. Additionally a visualization component is available to explore the results interactively on the screen. The software is designed in such a way that there exists no limitation regarding the geometric resolution, the size of the images or the definition of the spectral bands. This enables the examination of data from very different sources.

Figure 2: Software package

2.1 Integration of raster and vector data

For an efficient computation it is necessary that the GIS objects, which are represented in vector format, become converted into a raster representation to extract information very fast from the input channels or temporary intermediate results. A matrix is determined for each object which contains the raster representation of the object (see figure 3). The size of the matrix is dependent on the image resolution and the object size. Access on the pixels of the input images or intermediate results are possible with a simple Boolean operation.

2.2 Additional training areas

The basic idea of the approach is, to determine the typical spectral and textural characteristics of the land use classes from already collected GIS objects. This lead to good results if the number of correct collected objects is significantly higher than the number of wrong ones. However, it becomes problematic if very few objects or really no objects of a landuse class are contained in the image. If only few objects of a landuse class are contained in the image and some of this objects are additionally collected in a wrong way, too many wrong pixels are in the training areas and the classification result will be poor. If no objects at all of a land use class are contained in the image, a further processing of this land use class is not possible because no spectral or textural information are available.

For this reason it is possible to define a minimum number of training pixels for each landuse class. If there are less pixels than this minimum number, the according land use class is not evaluated and the objects of this land use class are not verified. In order to avoid this situation, it is possible to define up to three additional training areas in other images which are used if the number of training pixels is to low.

3 POTENTIAL

Not all object classes can be distinguished alone by their spectral and textural characteristics without addition of further information sources. Examples are the object classes wood and grove or residential area, industrial area and area of mixed use. Even a human operator is very often not able to distinguish these object classes without additional information. In addition, it is still added that the definition of these object classes in the object catalogue can be ambiguous and the object classes are often not clearly delimitable from each other. Therefore, object classes of this kind are combined together to one of the five different spectral classes: *greenland, forest, settlement, water* and *streets*.

4 INPUT DATA

The program was tested with ATKIS data sets and remote sensing data from very different sources. ATKIS is the German topographic cartographic spatial database [1] and presently contains more than 60 different feature types for the whole area of Germany in the scale of 1:25,000 (beside this scale there are further levels of data aggregation in the scales 1:200,000 and 1:1,000,000 which were not used in this work). The ATKIS data are the basis for a large number of applications in very different fields, like environmental planing, street information systems, forest monitoring and a lot more.

Results with data from the Indian Remote Sensing Satellite IRS-1C [15], the MOMS-2P camera system [13] which was used on the Russian MIR station, the Digital Photogrammetric Assembly (DPA camera system) [3, 6, 7] and from scanned analogue orthophotos can be found in [4, 5, 16, 17]. The quality of the results is dependent from three different factors: the geometrical resolution, the radiometrical resolution and the definition of the spectral bands.

In order to get interpretable and reliable results, a geometric resolution of 2 meter is sufficient for data in the scale 1:25,000. The problem of lower resolution data is that objects which are marked by the program as not found are very often not clearly visible in the image and therefore the results cannot be verified by an operator (see also [16, 17]). Higher resolution leads to better results especially in urban areas, but at the same time to a strong increase of the computing time.

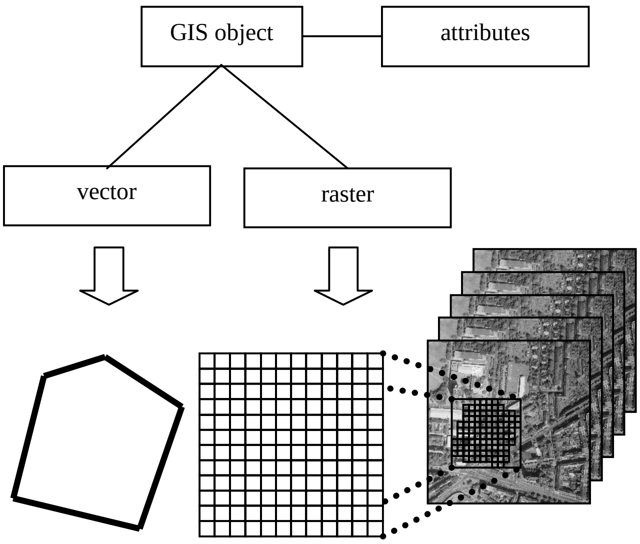


Figure 3: Raster representation of GIS objects

A radiometric resolution of 8 bit is sufficient for the classification to separate the different land use classes and is provided by most of the existing sensors. More important is the definition of the spectral bands of the sensor. A reliable classification of areas with strong shadow is only possible if a channel in the near infrared is available (see also [16, 17]).

In general it can be said that the higher the amount of information of the input data the better are the classification results. A very high information content can be achieved by integrating data with very different characteristics. This can be done for example by the combination of multispectral and laser data. Laser data improve the classification result significantly because they have a complementary "behavior" as multispectral data. With laser data the classes greenland and street can be separated very good from the classes forest and settlement because of the different heights of the pixels above the ground whereas in multispectral data the classes greenland and forest can be separated very good from the classes streets and settlement because of the strongly different percentage of chlorophyll.

The results presented in the following were computed with scanned CIR orthophotos plus laser data with a ground pixel size of 2 meters.

5 CLASSIFICATION

Image classification procedures are used to classify multispectral pixels into different land cover classes. The input for the classification are multispectral bands and textural patterns which are computed from the multispectral data (see for example [8]). There are numerous classification algorithms which can be divided into unsupervised and supervised approaches. In the unsupervised approach pixels are grouped into different spectral (and textural) classes by clustering algorithms without using prior information. After clustering, the spectral classes have to be associated with the land cover classes by an operator. Two basic steps are carried out in a supervised classification. In a training stage training areas have to be defined that describe typical spectral and textural characteristics of the data set. In the classification stage each pixel of the data set is categorized to a land cover class. There exist a lot of different approaches for the classification stage such as minimum-distance, parallel-epiped or maximum likelihood classification [11]. Very new approaches exist in the field of Neural Network Computing (see for example [2, 14]). The used approach in this project is a supervised maximum likelihood classification.

5.1 Training areas

The supervised classification requires a quantitative description of the spectral and textural characteristics (in form of training areas) of the different land cover classes in order to be able to assign unknown pixels to one of these classes. It is very important that the training areas contain as little as possible mixed pixels. Mixed pixels arise especially at object borders where two different objects are neighbored to each other. Therefore a buffer is computed around the object border. This buffer should be also broad enough to eliminate wrong pixels which can arise because of inaccurate data acquisition.

In ATKIS the street geometry is not captured by areas but by lines which represent the street centerlines. This leads to the fact that neighboring area objects of streets are captured not by their exact

Figure 4: Training areas

geometry but they are enlarged by the half width of the street (this is the ideal situation - if the captured middle axis is not exactly on the middle of the street this leads to a more inaccurate geometry of the neighboring objects). Therefore we generate a buffer around all streets and cut this out from the training areas.

Figure 4 shows the training areas for the land cover classes greenland, forest and settlement. Additional training areas for the classes water and street are generated from the ATKIS data.Training pixels for the class streets are not cut out as areas because streets are typically very narrow and long objects and consist therefore of many mixed pixels. Additionally, the acquisition accuracy is a very important factor as already mentioned above. From that fact only those pixels are taken which are located exactly on the middle axis of the ATKIS streets. A further problem are streets in forest areas. Since streets are mostly hidden in forests, no training areas are generated here at all. But also in other areas streets are often hidden by trees. In order to avoid wrong pixels here, the vegetation index can be used. All pixels which have a high vegetation index are removed from the training areas for streets.

5.2 Classification results

Figure 5 shows a classification result at an example. Forests are recognized being homogeneous and well detectable. Agricultural areas show sometimes inhomogeneities because of planting structures, but nevertheless they can be detected also very well. The land use class which could be detected best is water. The land use class settlement cannot be recognized as homogeneous uniform areas, but it is subdivided into several classes. It can be seen that pixels are only recognized as settlement areas if they represent house roofs. The other pixels are classified as streets, forest or agricultural area depending on the "ground truth". The reason for this result is the high resolution of 2m.

Figure 5: Classification result

6 MATCHING

After the classification it must be decided which of the GIS objects do not match the remote sensing data. This can be either objects where a change in the landscape has occurred or objects that were not collected correctly. All GIS objects are subdivided into three classes. The first class contains all objects which are detected with a high certainty in the remote sensing data, the second class contains all objects which are detected only partly and the third class contains all objects which cannot be detected at all. The decision to which class an object belongs is made by measuring the percentage of pixels which are classified to the same landuse class as the object itself. Optionally the form and the homogeneity of the correctly classified pixels are used. Very small or narrow objects are evaluated less strict than normal objects.

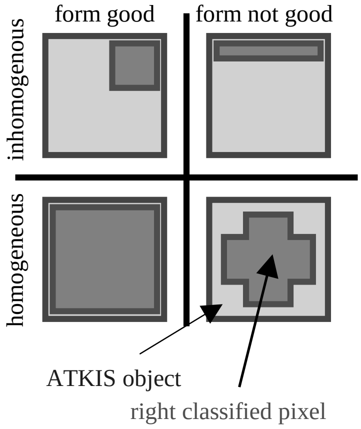


Figure 6: Measurement of homogeneity and form

6.1 Measures

Figure 6 shows by an example the measurement of the homogeneity and the form. The light gray rectangle represents an ATKIS object and the dark gray areas represent the pixels which are classified to the same object class as the ATKIS object. With the weighted sum of all three measures (percentage, homogeneity and form) the objects are subdivided into the classes full verified, partly verified and not found. The definition of the weights can be done interactively for each landuse class by the user.

6.1.1 Measurement of the homogeneity

With the homogeneity, a measure is defined which specifies whether the correct classified pixels are distributed uniformly in the object. For this, the distance of the center of gravity of all pixels of the object and the center of gravity of the right classified pixels is computed. The x-coordinate of the center of gravity CO_X of all pixels of an object is defined as:

$$CO_X = \frac{\sum_{all\_pixel} x\_position_{pixel}}{number(pixel)}$$

and the y-coordinate COy respective. The x-coordinate of the center of gravity CP_X of the right classified pixels is defined as:

$$CP_X = \frac{\sum_{right\_classified\_pixel} x\_position_{pixel}}{number(right\_classified\_pixel)}$$

and the y-coordinate CPy respective. The distance between these two centers of gravity is a measure of the homogeneity of the classification result. If the distance is large, the right classified pixels are distributed inhomogeneous in the object. This measure has to be normalized, because the distance is also a function of the object size. Therefore the distance is divided by the square root of the number of all pixels of the object:

$$homogeneity = \frac{\sqrt{(CO_X - CP_X)^2 + (CO_Y - CP_Y)^2}}{\sqrt{number(pixel)}}$$

6.1.2 Measurement of the form

The variance in x-direction VOx of all pixels is computed to describe the form of an object:

$$VO_X = \frac{\sum_{all\_pixel} (x\_position_{pixel} - CO_x)^2}{number(pixel) - 1}$$

and the variance in y-direction VOy of all pixels respective.The variance in x-direction VPx of all right classified pixels is computed in the same way:

$$VP_X = \frac{\sum_{right\_classified\_pixel} (x\_position_{pixel} - CK_x)^2}{number(right\_classified\_pixel) - 1}$$

and the variance in y-direction VPy of all right classified pixels respective. The ratio between the variances VO_X and VO_Y describes as a approximation the $form_O$ of an object:

$$form_O = \frac{VO_x}{VO_y}$$

and the form of the right classified pixel $form_P$ respective. In order to compare the form of the pixels of the object with the form of the right classified pixels the ratio of the two measures is calculated:

$$form = \frac{form_O}{form_P}$$

If this ratio is one, the form of the object and the right classified pixels is similar. If it is smaller or greater than one the form differs. For a better comparability the form is transformed in the interval [1, inf]:

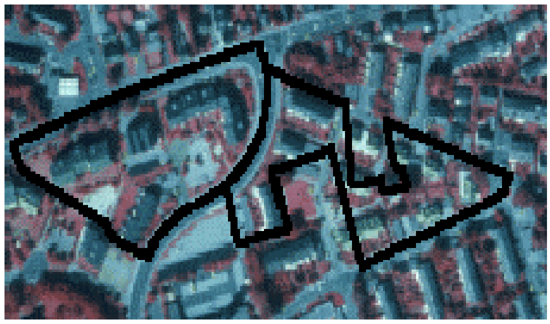
$$form = \begin{cases} \frac{form_O}{form_K} & \text{if } \frac{form_O}{form_K} \geq 1 \\ \frac{form_K}{form_O} & \text{else} \end{cases}$$

6.2 Matching results

Figure 7 shows an example of objects which could not be verified by the matching. The two objects which are superimposed in black on the image were collected as greenland in the ATKIS database. It can be seen that meanwhile a settlement area was built up. The result of the matching is that these two objects cannot be found in the image because of the low number of pixels that were classified as greenland.

Figure 8 shows an object that was collected as an greenland. But this object contains also a house and some paved areas which are represented in the classification result as settlement and street. The result of the matching is that this object can be verified only partly because the percentage of right classified pixels is too low and they are not distributed homogenous in the object.

cir image



classification

Figure 7: Example 1

7 SUMMARY

In this paper an approach is introduced which enables the automatic detection of changes in GIS databases by using remote sensing data. The approach is implemented in a software package under UNIX and X11 Windows. The program was designed in such a way that it is possible to use data from very different sources as an input. The best results can be achieved with the combination of multispectral and laser scan data. If these two data sources are available, a geometric resolution of 2m is sufficient to verify objects in the scale 1:25.000.

Whereas the classification is very robust, problems can appear by the matching process. The reason for this is, that ATKIS objects are not only collected from orthoimages but also from cadastral

cir image classification

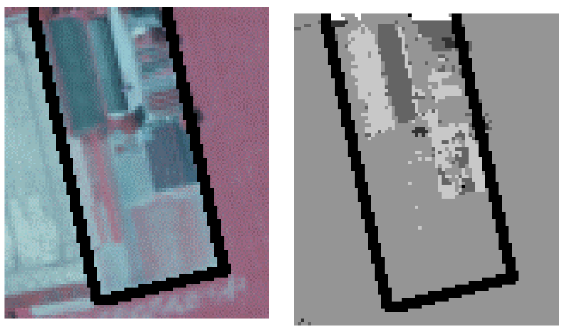


Figure 8: Example 2

maps. Therefore the acquisition of object borders is often done according to ownership structures and not according to detectable structures in the image. Additionally the object classes are defined in the object catalogue in such a way that very inhomogeneous objects can appear. An example for this statement can be seen in figure 8. The greenland object does not only contain greenland areas but also a farm house and some paved areas. This object is collected correctly according to the ATKIS object catalogue but it is so inhomogeneous that it cannot be verified by the matching. A solution for this problem would be to store the classification result for all objects in a data base. If an object could not be verified, the program can look into the database and compare the current classification result with an older one. If the two classification results are similar and an operator had already confirmed earlier that the object is correct digitized, it could be assumed that the object is still correct.

Acknowledgement

This research is carried out by order of the Surveying Institute of the State of Northrhine-Westphalia, Germany. The project is supported by the German Aerospace Center (DLR). The financial support of both institutions is gratefully acknowledged.

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